Linear_regression_report

Team: Who's there

Introduction

The aim of the project was to be able to find a model that best predicts the relationship between:

- the number of people counted with the survey for a given class at a particular hour
- Wi-fi log counted in that room at that hour

This will allow to see whether Wi-Fi log is a good predictor for estimating room occupancy.

We first tried to see if the relationship between these two variables was linear. To do so we run a linear regression.

Below we describes step by step all the analysis performed.

First of all, we set up the connection to the database, using the following code:

```
connection <- dbConnect(MySQL(),user="root", password="",dbname="who_there_db", host="localhost")
```

Then we made a query to the database, in order to get all the groundth truth data collected in room B.002, B.004 and B.006 from 9 to 17 and the correspondent Wi-Fi Log measured in that time frame and rooms.

The dataset created had in total 216 rows and it will allow us to explore if Wi-Fi log is a good predictor of the observed occupancy of the room in a certain hour.

As a **target features** for our linear regression we decided to use the number of associated client, calculated by multiplying the percentage of the room with the capacity of the room.

As response variables or feature we considered Wi-Fi logs, which were summarised either as average of the logs counted for each room and for each hour or as maximum of the logs measured for each room and for each hour.

Together with the Wi-Fi log, we included in the data set the following features:

- **Date**, which we did not use in this analysis, because they just cover 2 weeks of Novemeber, but for future analyses they can be used to group observations by seasons or semesters or to finds seasonal trends for time series analyses.
- **Time**, which will be explored either as continous variable and as categorical to explore if the time of the day can have an affect on the Wi-Fi log. To do so, we binned the time in 4 ranges: early morning (9-11), late morning (11-13), early afternoon (13-15) and late afternoon (15-17). This allowed us to see if the Wi-Fi log accuracy was changing during the day. For example, it is more likely that all the electronic devices are fully powered early in the morning and consequently the Wi-fi log data can be more accurate or overestimating the occupancy of the room (i.e. more than one device per person). On the contrary in the afternoon, the devices may be more likely to be out of battery and it is possible that there are less devices in the room.
- **Module**, which we are not going to include it in the analysis because the majority of the module present are for computer science. For future analyses it will be possible to explore if the accuracy of Wi-fi log in predicting the occupancy change across the courses. Science courses (especially computer science courses) will be more likely to use electronic devices during lectures than art students.

- **Course level**, which can indicate us whether electronic devices will be less used during different course levels. For example, first and second level courses can be more theoretical than the upper levels. Therefore, we might expect less connections. However, undergraduates might be more distracted during lectures and look at their phones. This will result in an increase of connections in that hour.
- **Tutorial**, which can affect the number of logged people. First of all, because tutorial divided the room in 2 and therefore there will be measured less people than expected.
- **Double_module**, categorical variable indicating whether in the class there are more than one module, increasing the number of people expected in the room.
- **class_went_ahead**, categorical variable indicating whether in the class went ahead to check for false positive.

The resulting data set is printed below:

```
head(AnalysisTable)
```

```
##   Room       Date Time    Module Course_Level Tutorial Double_module
## 1    1 2015-11-03    9         0            0        0             0
## 2    1 2015-11-04    9 COMP30190            3        0             0
## 3    1 2015-11-05    9         0            0        0             0
## 4    1 2015-11-06    9 COMP30220            3        0             0
## 5    1 2015-11-09    9 COMP30190            3        0             0
## 6    1 2015-11-10    9         0            0        0             0
##   Class_went_ahead Capacity Percentage_room_full Wifi_Average_logs
## 1                1       90                 0.00            4.7500
## 2                1       90                 0.25           13.4545
## 3                1       90                 0.00            6.8333
## 4                1       90                 0.00            2.4167
## 5                1       90                 0.25           14.7273
## 6                1       90                 0.00            2.2727
##   Wifi_Max_logs Survey_occupancy   Factor_Time
## 1            21              0.0 Early Morning
## 2            15             22.5 Early Morning
## 3            29              0.0 Early Morning
## 4             3              0.0 Early Morning
## 5            18             22.5 Early Morning
## 6            14              0.0 Early Morning
```

DATA QUALITY REPORT

Before running any analyses, we carried out the data quality report to check for any issue related to the variables (e.g. outliers, skewed distribution, NaN values) and we planned the solutions that we implemented to solve them.

Initially we set all the categorical variables as factors and then we printed the descriptive statistics for all the features.

```
##       Room       Date                Time          Module
##  Min.   :1   Length:216         Min.   : 9.00   Length:216
##  1st Qu.:1   Class :character   1st Qu.:10.75   Class :character
##  Median :2   Mode  :character   Median :12.50   Mode  :character
##  Mean   :2                      Mean   :12.50
```

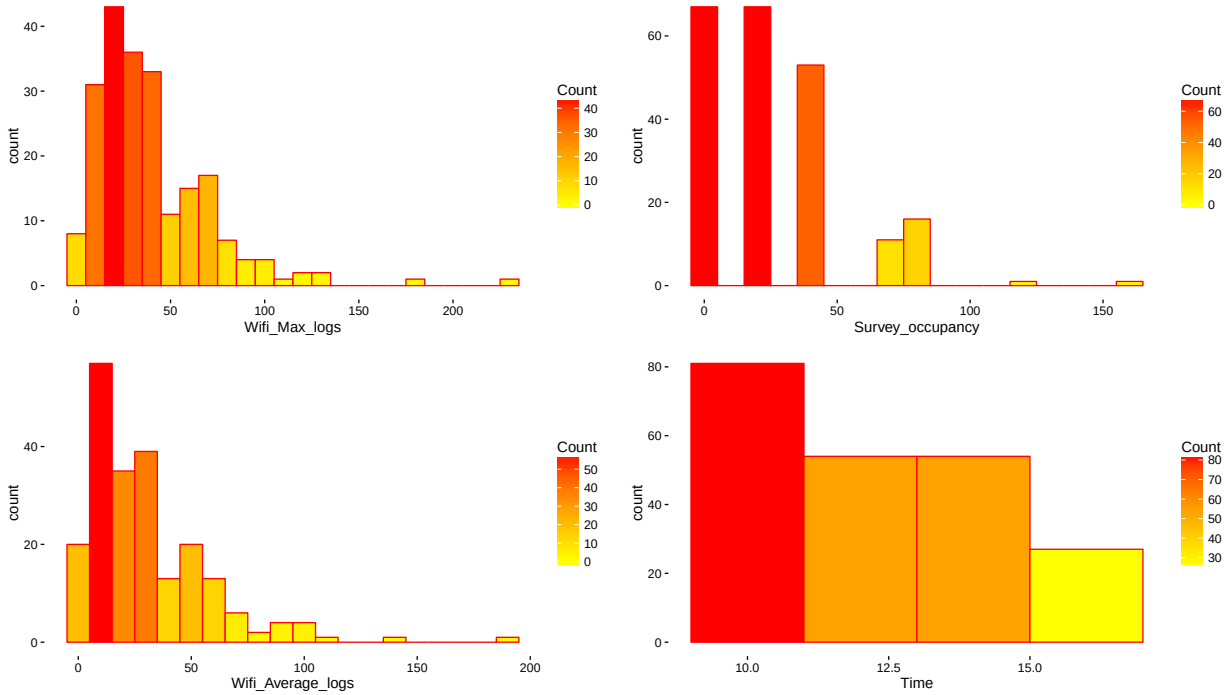
```
##  3rd Qu.:3                     3rd Qu.:14.25
##  Max.   :3                     Max.   :16.00
##  Course_Level    Tutorial      Double_module Class_went_ahead
##  0:59         Min.   :0.00000   0:210         0: 22
##  1:14         1st Qu.:0.00000   1:  6         1:194
##  2:23         Median :0.00000
##  3:76         Mean   :0.02778
##  4:40         3rd Qu.:0.00000
##  5: 4         Max.   :1.00000
##     Capacity     Percentage_room_full Wifi_Average_logs Wifi_Max_logs
##  Min.   : 90.0   Min.   :0.00         Min.   :  0.00    Min.   :  0.00
##  1st Qu.: 90.0   1st Qu.:0.00         1st Qu.: 11.61    1st Qu.: 18.75
##  Median : 90.0   Median :0.25         Median : 23.67    Median : 32.50
##  Mean   :113.3   Mean   :0.25         Mean   : 30.33    Mean   : 40.01
##  3rd Qu.:160.0   3rd Qu.:0.25         3rd Qu.: 43.88    3rd Qu.: 55.25
##  Max.   :160.0   Max.   :1.00         Max.   :192.92    Max.   :230.00
##  Survey_occupancy          Factor_Time
##  Min.   :  0.00   Early Morning  :54
##  1st Qu.:  0.00   Late Morning   :54
##  Median : 22.50   Early Afternoon:54
##  Mean   : 28.01   Late Afternoon :54
##  3rd Qu.: 40.00
##  Max.   :160.00
```

From this we could see that NaN values were not present in the data set. We could notice that the observations for the features Tutorials and Double_model were not even distributed across the 2 levels of the variables. In fact, only 6 observations were present for tutorial class and for double module class. Therefore, we decided to discard both the features, because they will be not informative for the analysis. Similarly for the feature class_went_ahead the majority of the lectures did not have similar number of the observations across the features levels and we decided to discard it. Furthermore, for the variables Wifi_Average_clients, Wifi_Max_clients and Survey_occupancy it seems that there were few outliers, since the median is lower than the mean and the max values were far higher than the mean values. We explored this issue with histograms and boxplots.

Exploratory graphs

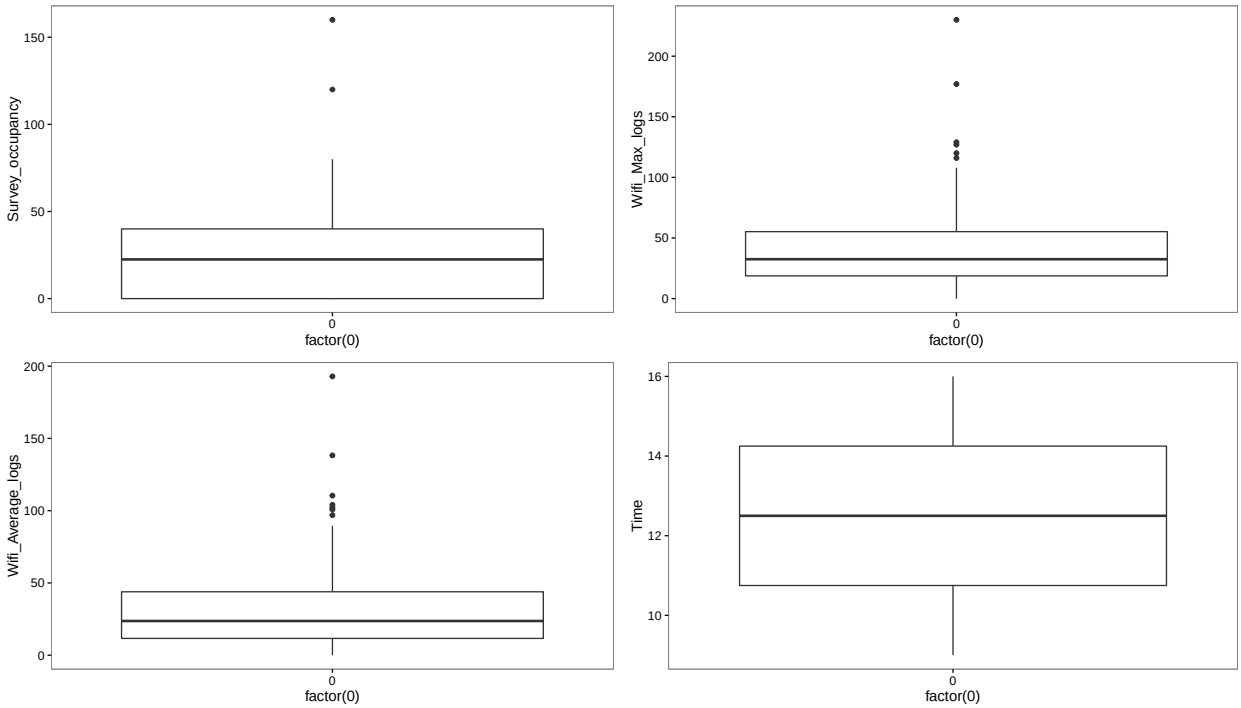
For exploring possible issues related with the continuous variables we plotted histograms and boxplots.

Histograms



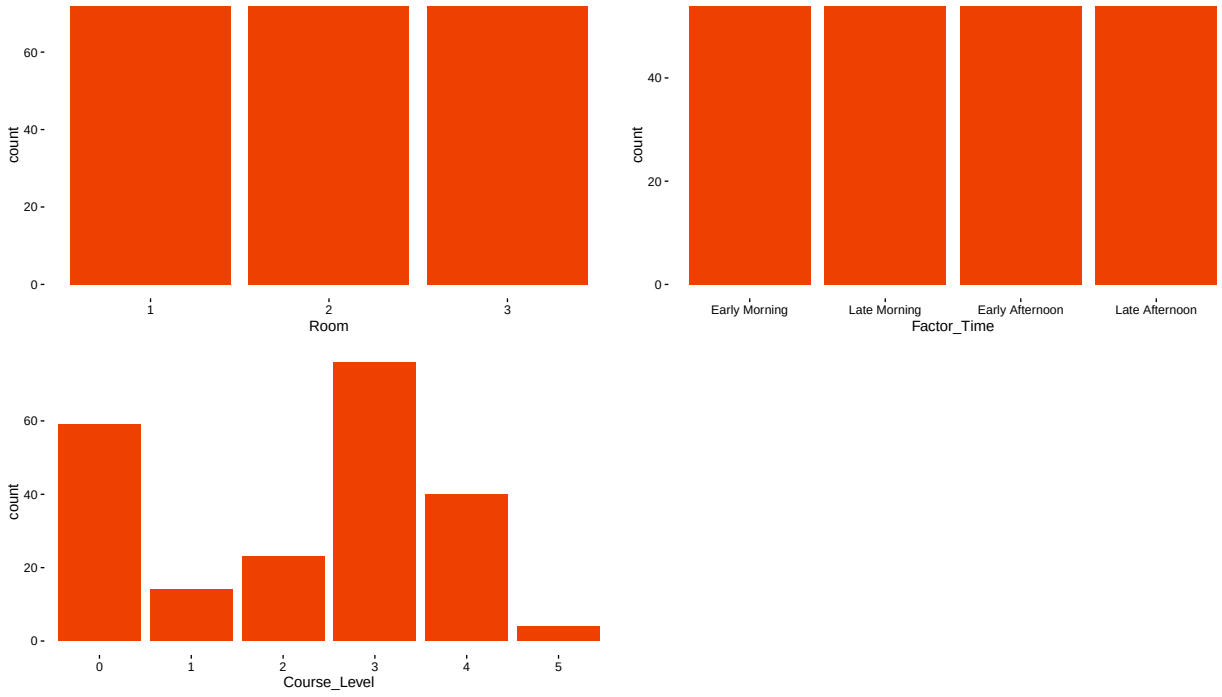
Form the histograms we could see that the distribution of the feature Wifi Maximum_client (i.e. the Maximum number of devices logged in one hour lecture) was skewed to the left, indicating that no more than 40 people attended the majority of the lectures. Furthermore, we could see that there were potential outliers (values $>$ 140). Similar patterns were observed for the feature Wifi_Average_clients. Different was the situation of the target feature, Survey_counted client, which showed a skewed distribution, but more scattered, similar to a Poisson distribution. This could cause a problem in running a linear regression and more likely we have have to run a generalise linear model with a Poisson distribution. This is not surprising, since we are dealing with count data (Zuur et al. 2009). Feature times had as well a skewed distribution, suggesting that the majority of the lectures were concentrating during the early morning and they were decreasing towards the afternoon.

Box plots.



From the boxplots, all the trends observed in the histograms were confirmed. For categorical variables we plotted bar plot graphs.

Bar plots.



From the barplots, we could see that observations were equally distributed across all the levels of the feature

Room and Factor Time. On the contrary, there were more observations for non lectures and level 3 courses. No issues were detected for those features.

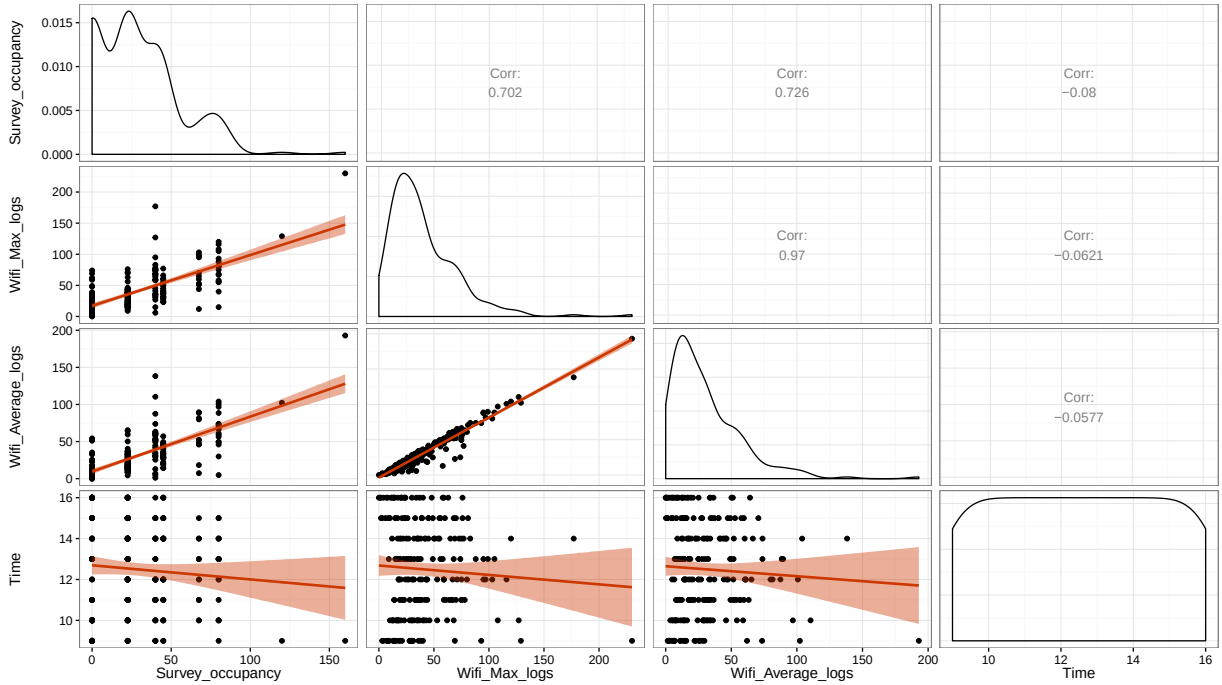
Summary.

Features	Issues	Planned Solution
Room	None	None
Time	Distibution skewed to the left	To solve during analysis
Factor Time	None	None
Course level	None	None
Tutorial	Uneven representation of the level	Discarded from the analysis
Double Module	Uneven representation of the level	Discarded from the analysis
Class went ahead	Uneven representation of the level	Discarded from the analysis
Wifi Average clients	Distibution skewed to the left & outliers	To solve during analysis
Wifi Maximum clients	Distibution skewed to the left & outliers	To solve during analysis
Survey Counted clients	Distibution skewed to the left & outliers	To solve during analysis

FEATURES AFFECTING THE TARGET FEATURE

The next step of the analysis was to see which features were more likely determining the occupancy of the class.
For the continuous features we explored the effects on the target features using a correlation matrix, while for the categorical features we used box plots.

Correlation matrix for continuous variables.



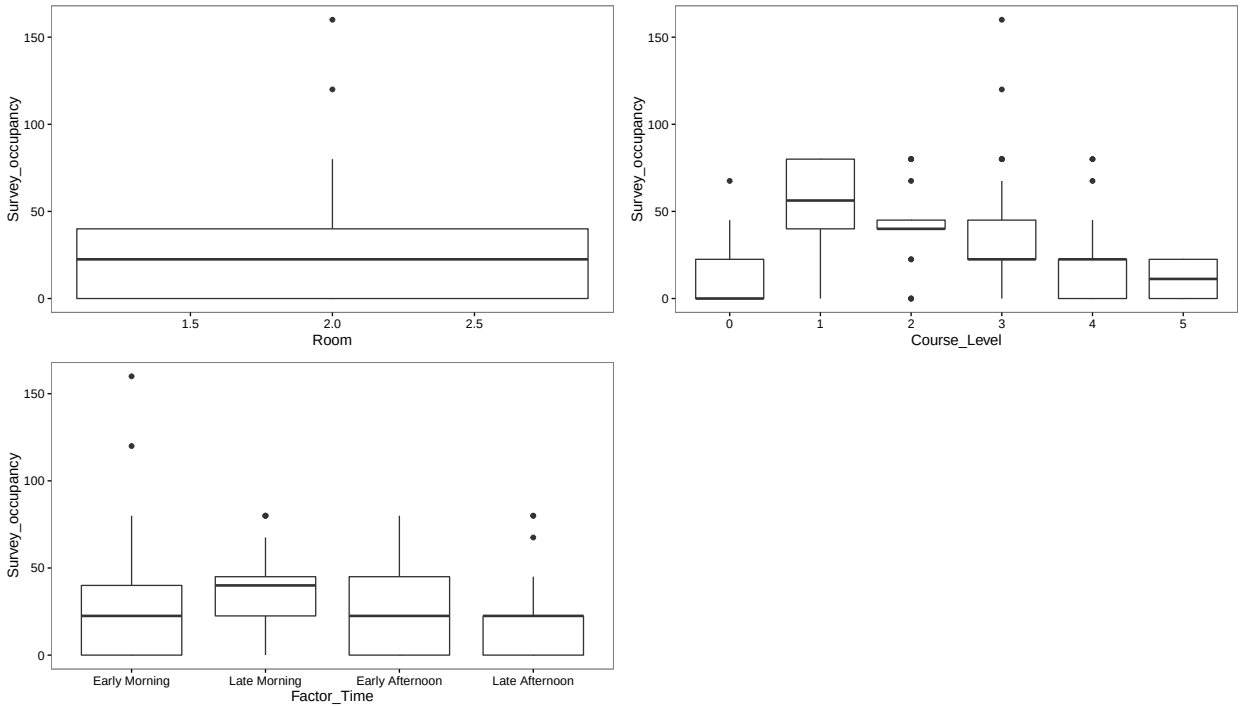
From the correlation matrix Survey counted clients seems to have a good correlation with Wifi Average counted clients and Maximum counted clients, therefore we are will try to run 2 models: one for exploring

the relationship between Survey counted clients and Average counted clients and another for Survey counted clients and Maximum counted clients. However, from this graphs we can see that there are 2 point that are clearly two outliers. Therefore, we are going to run the analyses with and without them to see if there is an improvement of the analysis without them.

From the graphs we can see that Average counted clients and Maximum counted clients are highly correlated showing that both of them are not so different. Therefore we will not expect too much difference among the 2 models.

Time does not seems to be correlated with the target features Survey counted clients and it seems more categorical.

Box plots for categorical variables.



From the boxplot plotting the counted people in the different room, it can be observed that the average of the counted people in room 1 was not different from room2. Room3 had an higher number of people on average, but this can be due to the outlier. The average number of counted people, instead, changed across the different course levels and it will be worth to explore if the occupancy of the room was affected by the course level. The highest average number of counted people was in the late morning around 50, while it was around 30 for the rest of the day. Therefore it will be interesting to explore the effect of the time on the occupancy.

Analysis

For selecting the features that together with the max logs or with the average logs best predict the ground truth data we will do model selection with a method similar to the one used by James et al. (2013).
For doing so, instead, of using the function *regsubset* for selecting all the possible models, we decided to considered the following models, because they better suits our hypothesis:

- *Survey occupancy ~ 1*, the null model;

- *Survey occupancy ~ Average Wifi occupancy*, for testing whether average Wi-Fi counting logs were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Room*, for testing whether average Wi-Fi counting logs and the room were were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Time*, for testing whether average Wi-Fi counting logs and the time of the day were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Course_Level*, for testing whether average Wi-Fi counting logs and course levels were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Room + Time*, for testing whether average Wi-Fi counting logs, room type and the time of the day were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Room + Course_Level*, for testing whether average Wi-Fi counting logs, room type and course levels were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Time + Course_Level*, for testing whether average Wi-Fi counting logs, the time of the day and the course levels were accurately predicting the occupancy of the room;
- *Survey occupancy ~ Average Wifi occupancy + Room + Time + Course_Level*, for testing whether average Wi-Fi counting logs, rooms, the time of the day and the course levels were accurately predicting the occupancy of the room;

The same models were run also with the occupancy estimated with the Maximum number of logs measured in that hour. All these models were run using the k-fold cross validation. K-fold validation was preferred over the validation set approach and the Leave Out Cross Validation (LOOCV), because it is more robust and more accurate in estimating the test error. The Validation set approach tends to give an over estimate of the test error and the test error is dependent on the observations included randomly in the test set. Furthermore, the LOOCV tends to provide a test error with a high variance, because the folds used to calculating it are correlated among each other. In particular in this analysis we are going to perform a 10-fold cross validation, which is pretty standard.

The 10 fold cross validation was carried out with the package, CVglm. For each model we estract the overall mean square error(MSE) and we picked as best model the model with the lowest MSE.

CASE1: Wi-Fi Average logs

All the models ran with the response variable Wifi average logs are summarised in the following table showing their MSE.

Models	MSE
Survey_occupancy ~ 1	711.234
Survey_occupancy ~ Wifi_Average_logs	343.184
Survey_occupancy ~ Wifi_Average_logs + Room	351.273
Survey_occupancy ~ Wifi_Average_logs + Factor_Time	354.343
Survey_occupancy ~ Wifi_Average_logs + Course_Level	366.148
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time	362.076
Survey_occupancy ~ Wifi_Average_logs + Room + Course_Level	374.665
Survey_occupancy ~ Wifi_Average_logs + Factor_Time + Course_Level	379.286
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time + Course_Level	387.614

As you can see from the table the model with the lowest MSE was the model with only the Wifi average logs as response variable.

CASE 2: Wi-Fi Maximum logs

We run the same models with the max WiFi logs as response variable, in order to see if it was a better predictor than the average WiFi logs.

Models	MSE
Survey_occupancy ~ 1	711.234
Survey_occupancy ~ Wifi_Max_logs	372.782
Survey_occupancy ~ Wifi_Max_logs + Room	381.25
Survey_occupancy ~ Wifi_Max_logs + Factor_Time	385.794
Survey_occupancy ~ Wifi_Max_logs + Course_Level	391.666
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time	393.896
Survey_occupancy ~ Wifi_Max_logs + Room + Course_Level	399.518
Survey_occupancy ~ Wifi_Max_logs + Factor_Time + Course_Level	406.344
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time + Course_Level	414.049

The model with the lowest MSE was the model: Survey_occupancy ~ Wifi_Max_logs. However, its MSE was slightly higher than the previous best model. Therefore we are going to run the Survey_occupancy ~ Wifi_Average_logs on the whole dataset.

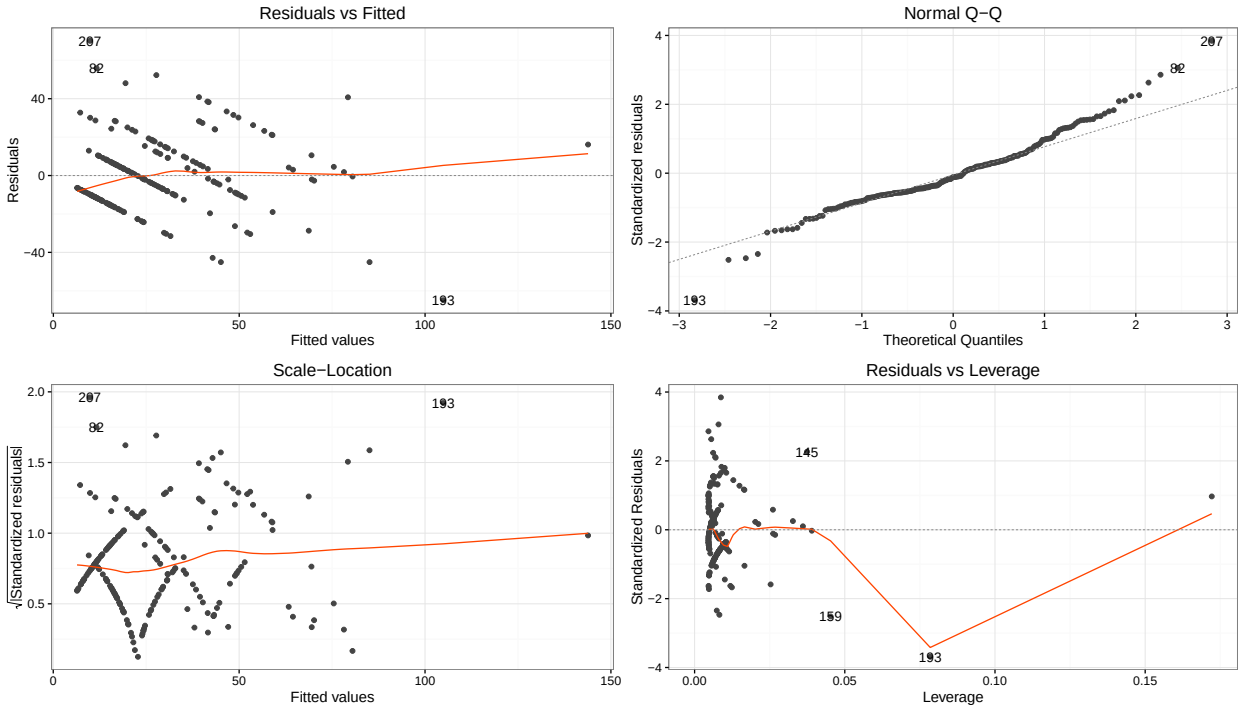
Looking at the model summary, the Wifi_Average_logs were significantly related to the Survey ground truth data.

```
summary(occupancy.lm.avg)
```

```
##
## Call:
## lm(formula = Survey_occupancy ~ Wifi_Average_logs, data = AnalysisTable)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -64.90 -10.97  -2.13   9.17  70.16
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         6.3992     1.8744    3.41  0.00077 ***
## Wifi_Average_logs   0.7125     0.0461   15.44  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.3 on 214 degrees of freedom
## Multiple R-squared:  0.527,  Adjusted R-squared:  0.525
## F-statistic:  238 on 1 and 214 DF,  p-value: <2e-16
```

However when we looked at the residuals plotted, there were few issues. As it could be seen below from the plot, showing the fitted values plotted againist the residuals, the target features had a lot values closed together similarly to what expected from a categorical features and there were a potential outliers (fitted values > 140). The observations seemed normally distributed, but the variance did not seem homogeneous.

```
## [1] "ggmultiplot"
## attr(,"package")
## [1] "ggfortify"
```



Removing the outliers

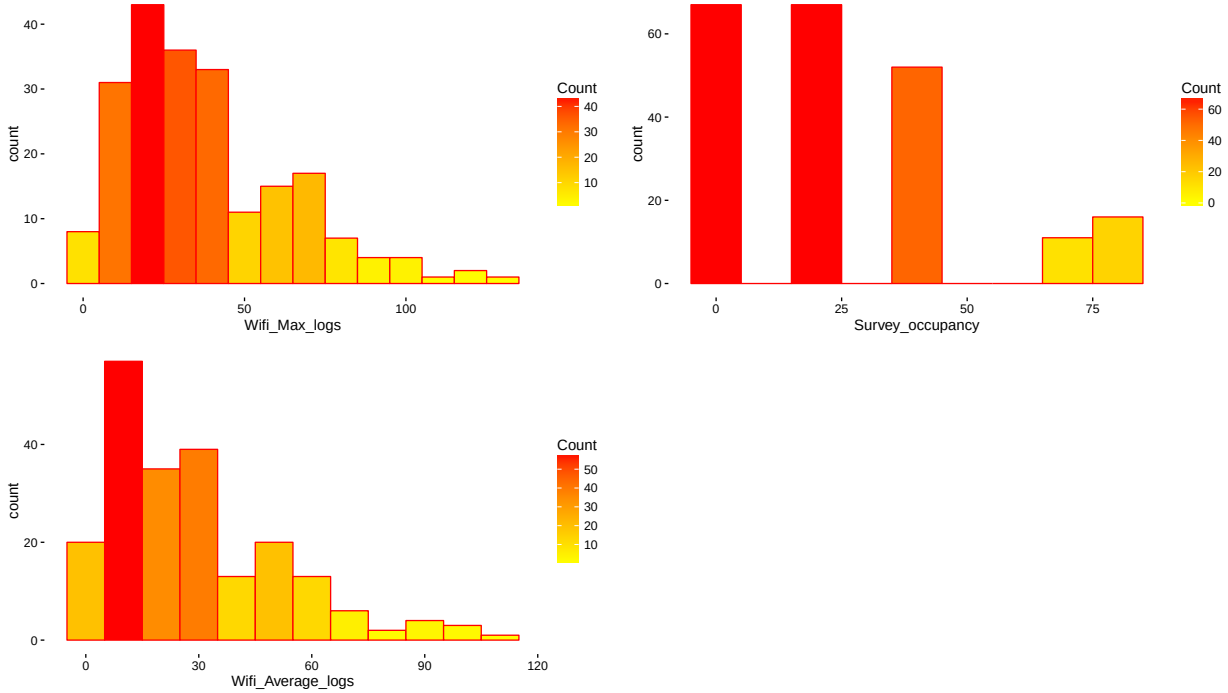
For deciding which observations remove, we looked at the histograms (see above), which showed that for Wi-fi Average logs and Maximum logs had potential outliers when the values were higher than 140, while for the Survey occupancy observations higher than 120 seemed outliers. Only 3 observations were removed and we did not lose too much data.

```
## [1] 213  14
```

```
##       Room          Date                Time         Module
##  Min.   :1.00   Length:213         Min.   : 9.0   Length:213
##  1st Qu.:1.00   Class :character   1st Qu.:11.0   Class :character
##  Median :2.00   Mode  :character   Median :13.0   Mode  :character
##  Mean   :1.99                      Mean   :12.5
##  3rd Qu.:3.00                      3rd Qu.:15.0
##  Max.   :3.00                      Max.   :16.0
##  Course_Level    Tutorial     Double_module Class_went_ahead    Capacity
##  0:59         Min.   :0.000   0:209         0: 22            Min.   : 90
##  1:13         1st Qu.:0.000   1:  4         1:191            1st Qu.: 90
##  2:23         Median :0.000                                  Median : 90
##  3:74         Mean   :0.028                                  Mean   :113
##  4:40         3rd Qu.:0.000                                  3rd Qu.:160
##  5: 4         Max.   :1.000                                  Max.   :160
##  Percentage_room_full Wifi_Average_logs Wifi_Max_logs   Survey_occupancy
##  Min.   :0.000        Min.   :  0.0     Min.   :  0.0   Min.   : 0.0
```

```
##  1st Qu.:0.000        1st Qu.: 11.5     1st Qu.: 18.0   1st Qu.: 0.0
##  Median :0.250        Median : 22.9     Median : 32.0   Median :22.5
##  Mean   :0.244        Mean   : 28.7     Mean   : 38.1   Mean   :26.9
##  3rd Qu.:0.250        3rd Qu.: 41.2     3rd Qu.: 54.0   3rd Qu.:40.0
##  Max.   :0.750        Max.   :110.4     Max.   :127.0   Max.   :80.0
##           Factor_Time
##  Early Morning  :52
##  Late Morning   :54
##  Early Afternoon:53
##  Late Afternoon :54
##
##
```

The histograms were re-plotted to see whether there was an improvement.



The histograms for the Wi-Fi logs seemed improved, while Survey data were still scatterd similar to a Poisson distribution. We decided to run the linear regression and see if there was any improvements.

CASE 1: Model selection with the dependent variable Wi-Fi average logs without outliers

All the models ran with the dependent variable Wifi average logs are summarised in the following table showing their MSE.

Models	MSE
Survey_occupancy ~ 1	593.138
Survey_occupancy ~ Wifi_Average_logs	314.55
Survey_occupancy ~ Wifi_Average_logs + Room	316.309
Survey_occupancy ~ Wifi_Average_logs + Factor_Time	320.687
Survey_occupancy ~ Wifi_Average_logs + Course_Level	330.378
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time	321.859
Survey_occupancy ~ Wifi_Average_logs + Room + Course_Level	332.303

Models	MSE
Survey_occupancy ~ Wifi_Average_logs + Factor_Time + Course_Level	336.909
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time + Course_Level	338.14

CASE 2: Model selection with the dependent variable Wi-Fi maximum logs without outliers

The best model was again the model with only the average logs as dependent variable. The MSE was slighty improved from the first time.

Models	MSE
Survey_occupancy ~ 1	593.138
Survey_occupancy ~ Wifi_Max_logs	336.665
Survey_occupancy ~ Wifi_Max_logs + Room	338.298
Survey_occupancy ~ Wifi_Max_logs + Factor_Time	344.145
Survey_occupancy ~ Wifi_Max_logs + Course_Level	346.838
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time	345.228
Survey_occupancy ~ Wifi_Max_logs + Room + Course_Level	348.401
Survey_occupancy ~ Wifi_Max_logs + Factor_Time + Course_Level	354.54
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time + Course_Level	355.206

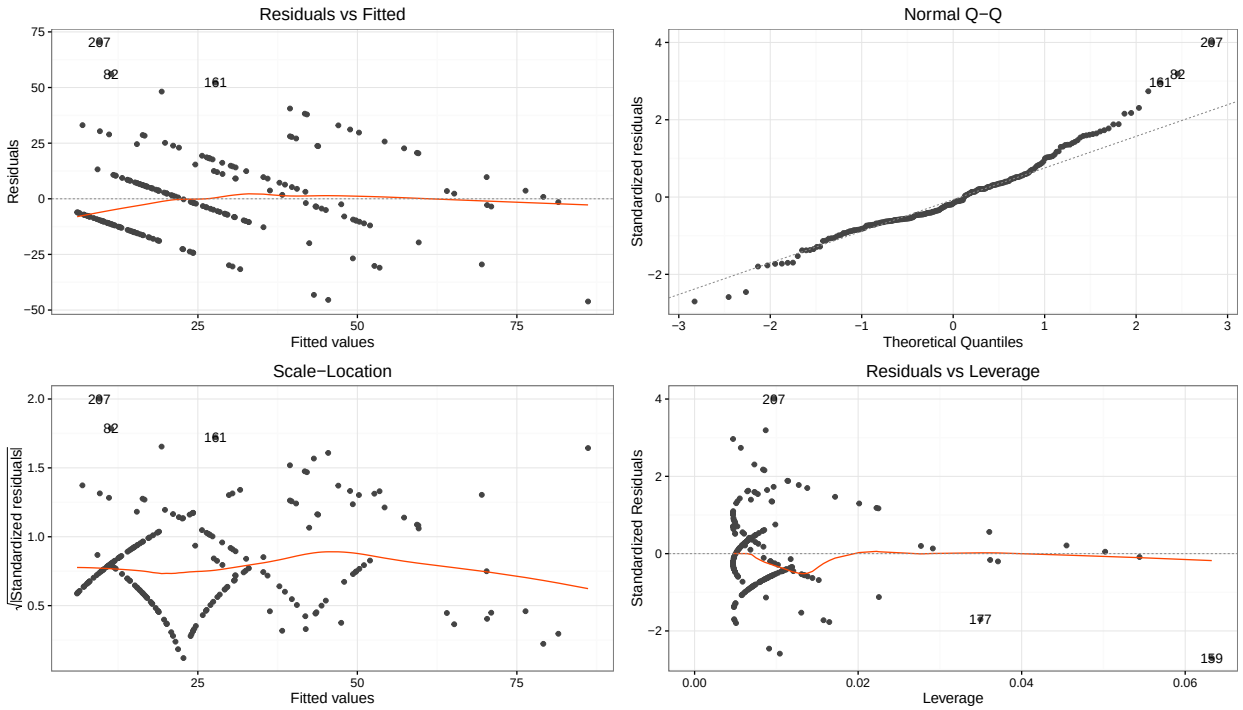
The model with the lowest MSE was the model with only the Wi-Fi Max logs as response variable, which was slightly higher than the Wi-Fi Average best model. Therefore we are going to run the Survey_occupancy ~ Wifi_Average_logs on the whole dataset.

Looking at the model summary, the Wifi_Average_logs were significantly related to the Survey ground truth data.

```
##
## Call:
## lm(formula = Survey_occupancy ~ Wifi_Average_logs, data = NoOutlierTable)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -46.16 -10.84  -2.83   8.56  70.43
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         6.0684     1.9280    3.15   0.0019 **
## Wifi_Average_logs   0.7253     0.0523   13.87   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17.6 on 211 degrees of freedom
## Multiple R-squared:  0.477,  Adjusted R-squared:  0.475
## F-statistic:  192 on 1 and 211 DF,  p-value: <2e-16
```

However when we looked at the residuals, there were few issues. From the plot looking at the residual vs fitted values, we still could see that the Survey occupancy was assuming more or less the same values and this explain the line pattern of the graphs. The data were quite normal distributed, but the variance did not seem homogeneous.

```
## [1] "ggmultiplot"
## attr(,"package")
## [1] "ggfortify"
```



Since the logaritmic transformation of the target features did not work, we ran a generalised linear model with a quasi-poisson GLM model, because the Poisson model suffered of overdispersion.

GENERALISED LINEAR MODEL WITH POISSON DISTRIBUTION

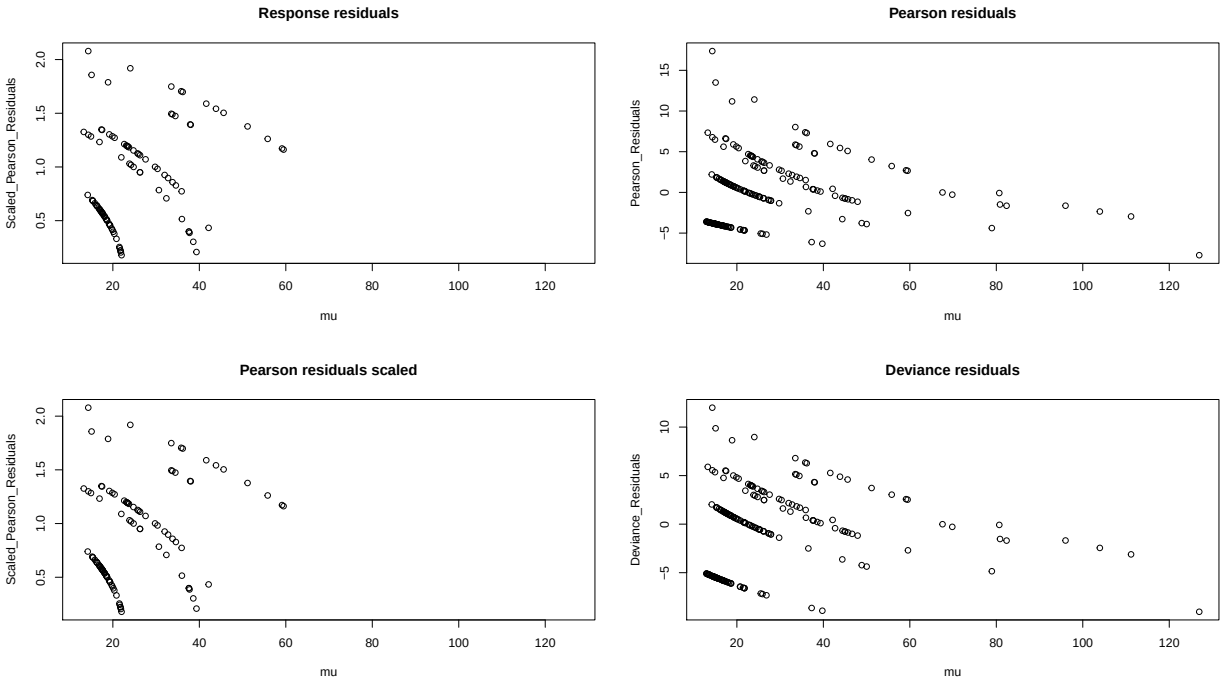
We run all the models using the package glm with family quasi-poisson and cv.glm for running 10-fold cross validation and we took the model with the lowest raw cross-validation estimate of prediction (delta) as best model.

Models	Adjusted delta
Survey_occupancy ~ 1	596.145
Survey_occupancy ~ Wifi_Average_logs	389.82
Survey_occupancy ~ Wifi_Average_logs + Room	393.553
Survey_occupancy ~ Wifi_Average_logs + Factor_Time	390.722
Survey_occupancy ~ Wifi_Average_logs + Course_Level	407.9
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time	402.706
Survey_occupancy ~ Wifi_Average_logs + Room + Course_Level	399.967
Survey_occupancy ~ Wifi_Average_logs + Factor_Time + Course_Level	415.519
Survey_occupancy ~ Wifi_Average_logs + Room + Factor_Time + Course_Level	399.533

The best model was Survey_occupancy ~ Wifi_Average_logs with an adjusted cross-validation estimate of prediction error of 390. As for the linear regression we run all the model with the dependent variable Wifi_Max_logs.

Models	Adjusted delta
Survey_occupancy ~ 1	596.145
Survey_occupancy ~ Wifi_Max_logs	393.731
Survey_occupancy ~ Wifi_Max_logs + Room	396.005
Survey_occupancy ~ Wifi_Max_logs + Factor_Time	393.774
Survey_occupancy ~ Wifi_Max_logs + Course_Level	404.093
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time	409.073
Survey_occupancy ~ Wifi_Max_logs + Room + Course_Level	398.955
Survey_occupancy ~ Wifi_Max_logs + Factor_Time + Course_Level	408.063
Survey_occupancy ~ Wifi_Max_logs + Room + Factor_Time + Course_Level	404.388

The best model was Survey_occupancy ~ Wifi_Max_logs with an adjusted cross-validation estimate of prediction error of: 394, which was slightly worst than the model with the average logs as predictor. Therefore we are going to run Survey_occupancy ~ Wifi_Average_logs on the whole dataset. To validate the model we plotted the following residuals, as suggested by Zuur et al. (2009): Ordinal residuals, Pearson residual, scaled Pearson residuals (to take into account the overdispersion) and the deviance residuals for the optimal quasi-Poisson model applied on the dataset without outliers.

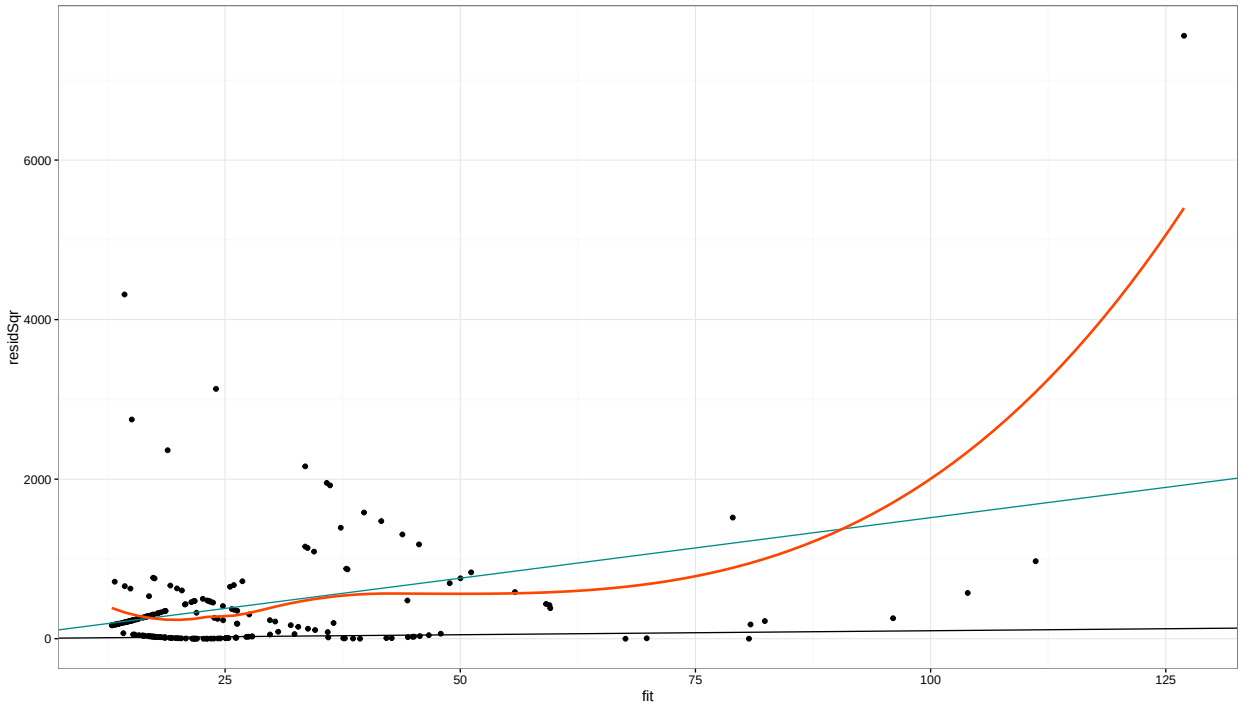


From all the residuals plot we could see a pattern, the residuals were decresing as the average or mu of the fited values were decreasing, suggesting that the quasi-poisson glm was not appropriate. For double checking it, we checked if the variance of the residuals was proportional to the mean, as suggested by this tutorial (https://www.ssc.wisc.edu/sscc/pubs/RFR/RFR_Regression.html). For doing so we plotted the residuals aganist the predicted mean and in this graph we plotted 3 lines:

- a black line representing the Poisson assumed variance;
- a blue plotting the quasi-Poisson assumed variance;
- orange curve for the smoothed mean of the square of the residual.

In theory the orange line should be straight and collinear with the blue line. Higher is the deviation of

the orange line from the blue one, higher is the chance that the variance of the quasi-Poisson model is not proportional to the mean as assumed by the model.



As we can see from the graph, the orange smoothed mean of the square of the residual is diverging from the Poisson assumed variance. For this reason, the quasi-poisson model was not appropriate for our data. Therefore, we decided to run the model using a negative bionomial distribution that it is designed to deal with overdispersion. The negative bionomial model, however, has a very high dispersion parameter and it was suited for our data. Therefore the linear model was selected as our best model.